

Workers' Attitude Towards Bus Rapid Transit: Considering Dhaka, Bangladesh**Sharmin Nasrin (Corresponding Author)****PhD Student****School of Civil Engineering and Built Environment****Science and Engineering Faculty****Queensland University of Technology, Brisbane, QLD, Australia.****Jonathan Bunker****Associate Professor****School of Civil Engineering and Built Environment****Science and Engineering Faculty****Queensland University of Technology, Brisbane, QLD, Australia.****Zuduo Zheng****Senior Lecturer****School of Civil Engineering and Built Environment****Science and Engineering Faculty****Queensland University of Technology, Brisbane, QLD, Australia.****Number of Words in Abstract, texts and reference: 4082****Number of Tables: 8****Submission Date: 27/07/2014**

Bus Rapid Transit in Dhaka City: A Stated Preference Approach

ABSTRACT The Government of Bangladesh is planning to develop and implement Bus Rapid Transit (BRT) in Dhaka city. This paper presents a stated choice survey conducted to understand workers' attitudes toward BRT in Dhaka. The survey data are analysed using a multinomial logit (MNL) model to scrutinize social and economic factors' impact on participant's mode choices. Analysis results reveal that males, and workers with higher age, education qualification, and income have greater tendency towards choosing BRT.

Keyword: Bus Rapid Transit, Dhaka, Multinomial Logit Model, Stated Preference

1. Introduction

Dhaka is the capital city of Bangladesh. Like other megacities Dhaka is experiencing serious traffic congestion (1). To reduce traffic congestion Government of Bangladesh is planning to implement BRT in Dhaka.

Research questions addressed in this paper are: 1) Will the majority of commuters choose BRT for their work trip once implemented, and 2) how do travel attributes, and socio-demographics act differently on workers' mode choice decisions in the context of Dhaka compared with developed cities?

As very limited research exist for understanding commuter travel behaviour and ultimately factors influencing BRT success in the context of a megacity in a developing country, this paper will have significant importance to practitioner and researcher.

This study uses a discrete choice modelling approach. A stated choice survey (SC) (i.e. hypothetical choice survey) was conducted in Dhaka from September 2011 to December 2012. As BRT has not yet been implemented in Dhaka, SC was chosen with a hypothetical BRT scenario amongst several choices for the work trip to understand important factors that have influence on workers' mode choice decisions. A mode choice model was developed using the SC data and "LIMDEP" software (2). Remaining of this paper starts with literature review, then describes design of the SC survey followed by modelling analysis and conclusions.

2. Literature Review

2.1 Travel Behaviour Elasticity

Elasticity is defined as the measure of a change in response to a change in attribute. Many published and unpublished elasticity values of travel time and travel cost of different modes are available from research on other cities (3). Elasticity values obtained from this research will be compared with elasticity value from European, US and Australian cities to understand the uniqueness of travel behaviour of a developing city like Dhaka. However, elasticity values for personalized public transport (PPT) (i.e., rickshaw and auto-rickshaw, which is named as CNG in Dhaka) are not available for developed cities, because such mobility options are unique features of a developing city like Dhaka. BITRE (3) provides a comprehensive dataset on transport elasticity. Elasticities obtained by other researchers are usually provided in three ways; short run (less than two years), medium run (within five years), and long run (more than five years). Analyses based on short and medium run elasticity tend to understate the result. According to Goodwin (4) and Litman (5) the long term impact would be twice the short term impact. Therefore, comparative analysis between very short run elasticity from this research and other cities will still provide indication uniqueness of travel behaviour in a developing city.

Balcombe, Mackett (6) reported the impact of different factors on public transport in context of UK. More specifically, elasticity of in-vehicle time for bus ranges from -0.4 to -0.6.

Dargay (7) compared transit elasticity between England and France from 1975 to 1990, and found that income rise did not negatively impact French people's decision to use public transport, whereas it did impact English people's. Dargay and Hanly (8) analysed demand for local bus service in England. They used a dynamic econometric model (separate short- and long-run effects) of per capita bus patronage, per capita income, bus fares and service levels. Their research found that commuters are relatively fare sensitive with wide variation of elasticity.

Deb and Filippini (9) determined elasticity values for twenty-two Indian states over the period from 1990 to 2001. Their research found that for all states public transport demand is inelastic with respect to fare.

Goodwin (4) produced average elasticities based on studies on UK and Europe. His research found that price impact will increase over time. Therefore, short run impact will be always less than long run.

Hague Consulting Group (10) discussed impact of car travel cost and car travel time mainly for European cities in the report conducted for the Trace project. Their research found that 10% change in car time has a bigger impact on trips and kilometres than a 10% change in car cost. Research finding also suggest that the short term elasticities of car km are more or less 50% of the long run counterparts.

Hensher and Louviere (11) drew on a 1994 data set collected in 6 Australian capital cities to estimate a series of commuter mode choice models in the presence and absence of two 'new' alternatives (light rail and busway systems), to derive matrices of direct and cross point elasticities for travel cost and travel time. Their research found that constraining the variance of the unobserved effects to varying degrees tends to over-estimate the elasticities sufficiently to distort the real behavioural sensitivity of specific attributes influencing choice.

Tsai, Mulley (12) identified public transport demand elasticity for Sydney, Australia. The research findings suggest that the public transport demand elasticity of price in Sydney is -0.22 in the short run and -0.29 in the long run.

Wallis and Schmidt (13) updated and re-examined transport demand elasticity from Australia and New Zealand.

The literature review suggest that there are many sources that produce original elasticity for different modes and many sources that compile elasticity from other's research. Table 1 lists the elasticity of travel time and in-vehicle travel time and Table 2 lists the elasticity of travel cost for different cities. However, no study was found which provides comparison of impact of travel factors between developed and developing cities. This research will provide a significant contribution to knowledge by providing a comparison between developed cities and developing cities travel difference in context of Dhaka city.

TABLE 1 Direct and Cross elasticity of travel time and in vehicle travel time of various modes from other studies

City relevant to study or project	Attribute	Direct Elasticity value	Cross Elasticity
Chicago ¹	Rapid Transit Travel Time	Direct elasticity of rapid transit -1.51	
Montreal ¹	Bus and rapid rail in vehicle travel time	Direct elasticity of Bus and rapid rail in vehicle travel time -0.27	
Australia ²	BRT travel time	Direct elasticity of BRT travel time -0.857	
Australia and New Zealand ³	Bus in-vehicle travel time	Direct elasticity of bus -0.50	
Karachi city in Pakistan Based on study of Thorbani (1984) ⁴	Bus in-vehicle time	Direct elasticity of bus -0.77	Cross elasticity of car 0.03 Cross elasticity of PPT 0.17 Cross elasticity of walk 0.06
Chicago city ⁵	Bus in-vehicle time	Direct elasticity for bus -1.10	
San Francisco ⁵	Bus in-vehicle time	Direct elasticity for bus ranges from -0.46 to -0.60	
Minneapolis ⁵	Bus in-vehicle time	Direct elasticity for bus -0.52	
Chicago ¹	Bus travel time	Direct elasticity of bus travel time -3.03	

City relevant to study or project	Attribute	Direct Elasticity value	Cross Elasticity
East Bay San Francisco ¹	Bus in vehicle travel time	Direct elasticity of bus in vehicle travel time -0.46	Cross elasticity of car in vehicle travel time 0.15
Australia and New Zealand ³	Car in-vehicle travel Time	Direct elasticity of car in short run -0.3 and in long run -0.6	
Karachi city in Pakistan Based on study of Thorbani (1984) ⁴	Car in-vehicle time	Direct elasticity of car -0.04	Cross elasticity of bus from 0.01 to 0.02
Great Britain ⁴	Car in-vehicle time	Direct elasticity of car -0.44	
Europe ³	Car in-vehicle time	Direct elasticity of car -0.62 for short run and -0.41 for long run	
Dutch National Model ¹	Car in-vehicle time	Direct elasticity of car -0.39 for short run and -0.58 for long run	Cross elasticity of bus 0.18 for short run and 0.16 for long run
Italian national model ¹	Car in-vehicle time	Direct elasticity of car -0.54 for short run and -0.56 for long run	Cross elasticity of bus 0.22
Model for Brussels ¹	Car in-vehicle time	Direct elasticity of car -0.23 for short run and -0.26 for long run	Cross elasticity of bus 0.38 for short run and 0.37 for long run
Chicago ¹	Car Travel Time	Direct elasticity of car travel time -0.64	
Minneapolis ⁵	Walk travel time	-0.26 for work trip -0.14 for non-work trip	

1 Source: ¹Hague Consulting Group (10); ²Hensher and Louviere (11); ³Wallis and Schmidt (13); ⁴BITRE (3); ⁵Lago, Mayworm (14)

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4 **TABLE 2 Direct and Cross Elasticity of Travel Cost of Different Modes from Other Studies**

City	Attribute	Direct Elasticity	Cross Elasticity
Chicago ¹	Rapid transit travel cost	Direct elasticity of rapid transit -0.17	
Australia ²	BRT fare	Direct elasticity of BRT -0.573	
Study on Leeds City ³	Public Transport travel cost	Direct elasticity of public transport is -0.65	Cross elasticity of car 0.14 Cross elasticity of walk is 0.56
Study on Dortmund City ³	Public Transport travel cost	Direct elasticity of public transport -0.58	Cross elasticity of car 0.12 Cross elasticity of walk is 0.23
Study on Tokyo City ³	Public Transport travel cost	Direct elasticity of public transport -0.03	Cross elasticity of car 0.09 Cross elasticity of walk 0.09
Study on UK and Europe ⁴	Bus fare cost	Direct elasticity of bus for short run -0.28 and for long run -0.55	
Study on Australia ¹	Bus fare cost	Direct elasticity of bus fare is -0.29	
Chicago ¹	Bus travel cost	Direct elasticity of bus -0.16	

City	Attribute	Direct Elasticity	Cross Elasticity
Study on Australia ⁵	Bus fare cost	Direct elasticity of bus from 0.18 to -0.22	Cross elasticity of car is 0.1
UK City ⁶	Bus Cost	Direct elasticity of bus in the short run from -0.2 to -0.3 Direct elasticity of bus in the long run from -0.4 to -0.6	
UK City ⁷	Bus Cost	Direct elasticity of bus in the short run -0.4 Direct elasticity of bus in the long run -1.0	
Sydney ⁸	Public Transport Fare	Direct elasticity of public transport -0.15	Cross elasticity of car 0.173
Sydney ⁹	Public Transport cost	Direct elasticity of public transport in the short run -0.22 long run -0.29	
Study on Leeds City ³	car travel cost	Direct elasticity of car -0.29	Cross elasticity of walk 0.06 Cross elasticity of Public transport 0.31
Study on Dortmund City ³	car travel cost	Direct elasticity of car for its travel cost -0.23	Cross elasticity of walk 0.41 Cross elasticity of Public transport 0.4
Study on Tokyo City ³	car travel cost	Direct elasticity of car -0.06	Cross elasticity of Public transport 0.03 Cross elasticity of walk 0.03
Chicago ¹	Car travel cost	Direct elasticity of car -0.28	
Sydney ⁸	Car cost	Direct elasticity of car -0.094	Cross elasticity of bus 0.08

1 Source: ³Luk and Hepburn (15); ⁵Hague Consulting Group (11); ¹Banister, Cullen (16); ²Goodwin (4); ⁴Booz Allen &
2 Hamilton (17); ⁶Dargay and Hanly (18); ⁷Balcombe, Mackett (6) ; ⁸Taplin, Hensher [(19); ⁹Tsai, Mulley [12]
3)

2.2 Model Choice Modelling for Dhaka and Other Developing Cities

Some studies have developed mode choice models in the context of Dhaka city ([20], [21], [22], [23], [24], [25], [26], [27]). However, only Enam [25] developed a mode choice model to perceive the preferences for mass rapid transit. Anam and Hoque [28] analysed current performance of existing bus services and justified and proposed bus rapid transit (BRT) road cross-section in an existing right of way (ROW). They compared the minimum requirement of BRT with corridor characteristics, existing roadway widths, condition, vehicular composition, land use pattern and obstacles along the corridor.

Nkurunziza, Zuidgeest [29] developed a binary choice model to understand commuters' preference for the proposed bus rapid transit in Dar-es-salam, Tanzania. Palma and Rochat [30] developed a NL model for the work trip of Geneva. They focused on the joint nature of the decision of number of cars to own in the household and the decision to use the car for the trip to work. Tushara, Rajalaksmi [31] developed a mode choice model for Cailcut, India by MNL model application. None of the research found in context of Dhaka city and very limited research in the context of developing cities provided acceptability of BRT considering users' perception. A mode choice model result will give indicative answer of users' expectations from the BRT system for a similar developing city like Dhaka.

3. Stated Choice (SC) Experiment

Statistical design considered for SC survey of this research is fixed choice set with full factorial orthogonal design. As BRT is not in operation in Dhaka, to understand workers' preference for BRT mode choice model with stated choice survey data is the most suitable.

In the SC survey participants assumed that they live 5 km from their usual work place and respondents were given a fixed choice set with description of all possible choice sets of 16 scenarios. Respondents were asked to choose only one choice from these 16 scenarios. Table 3 lists modes, attributes and their levels considered in the SC survey. SC survey was conducted on 426 samples. Each of the sample of the survey were contacted personally. Researcher explained BRT to samples with the BRT card. A paper based survey was the media chosen for its simplicity and convenience for face to face interaction. With internet usage still infrequent in Dhaka, web based surveying was not a feasible option. Survey by telephone was also not considered feasible due to high time and cost requirements. Glasow (32) stated that survey questions should be consistent with the education level of respondent. In this vein the survey was written in simple Bangla, which is easy to understand for most of the respondents, as well as English. Travel cost of Walk-BRT-Walk represent BRT fare as walking does not require any cost.

TABLE 3 Modes, Attributes and Their Levels in the SC Survey

Mode	Travel Time (min)	Travel Cost (US\$)
Walk-BRT-Walk	49.5; 44; 38.5; 33	0.06; 0.13; 0.16; 0.20
Walk-BRT-Rickshaw	45; 40; 35; 30	0.32; 0.40; 0.42; 0.45
Rickshaw-BRT-Rickshaw	40.5; 36; 31.5; 27	0.58; 0.64; 0.68; 0.71
Rickshaw	35	1.03
CNG	17	2.06
Car	14	3.87
Walk	45	0

In the initial run different BRT has been considered as individual modes with different comfort levels and different cost. However, model did not work out. In the paper "Workers travel behaviour in the developing countries megacity considering Dhaka as a case study" model result with Revealed preference data provide evidence that travel cost and travel time in motion are the main attributes for workers to choose different modes. Therefore, assumption has taken that comfort may not significantly influence the model result. That's why all BRT services have been merged into one to understand workers' preference for BRT as a whole. Table 4 lists comfort of BRT at different levels.

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TABLE 4 Different Levels of BRT for the SC Survey

Choice	Travel time (minute)	Bus Comfort
BRT Level 1 (This level is similar to current condition as bus service do not improve)	10% reduction of travel time of Bus from the current travel time (Current average bus speed ¹ 10 mph, current average bus cost ² 0.02 \$US/km)	<ul style="list-style-type: none"> • Buses have no fans • Buses have no proper seating arrangement • buses have level boarding • narrow bus doors • basic bus stands with shelters • crowded conditions but no service denials • buses arrive predictably at 25 min frequency
BRT Level 2	20% Reduction of Travel Time bus from the current travel time (Current average bus speed ¹ 10 mph, current average bus cost ² 0.02 \$US /km)	<ul style="list-style-type: none"> • Buses do not have fan • proper seating and standing arrangement • passengers do not have to climb the stairs to get into buses • doors are wide • very basic bus stand with shelter • crowded but condition improved from current condition so passengers can get into buses • buses are not unpredictable and comes every after 20 minutes
BRT Level 3	30% Reduction of Travel Time from the current travel time (Current average bus speed ¹ 10 mph, current average bus cost ² 0.02 \$US /km)	<ul style="list-style-type: none"> • Buses have fans • proper seating and standing arrangement • no need to climb stairs to board bus • wide doors • moderately crowded • bus stands upgraded with security camera and emergency phone • passengers can board buses easily • most passengers can sit • predictable bus frequency of 15 minutes
BRT Level 4	40% Reduction of Travel Time from the current travel time (Current average bus speed ¹ 10 mph, current average bus cost ² 0.02 \$US /km)	<ul style="list-style-type: none"> • All buses have air conditioning (AC) • proper seating and standing arrangement • buses are low lying, do not have to climb the stairs to get into buses • wide doors • very good quality bus; not crowded • bus stands are upgraded with security camera, emergency phone passenger information system • passengers can get into buses easily • most of the passengers can seat • buses are not unpredictable and comes every after 7 minutes

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¹ personal observation and assumptions from the survey responses and literature review.

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²Bangladesh Road Transport Authority [33]

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4. Multinomial Logit Model (MNL) Analysis FOR DHAKA

Multinomial logit choice model is based on maximum utility maximization theory [34, 35]. By MNL model the probability of choosing an alternative i from a set of j alternatives is expressed by Equation 1.

$$Pr(i) = \frac{\exp(v_i)}{\sum_{j=1}^J \exp(v_j)} \quad \text{Eq. 1}$$

Where,

$Pr(i)$ is probability of choosing alternative i

v_i is utility function of any mode

j is total number of alternatives

The choice of model depends on the characteristics of the data. With the exception of MNL model none of the modelling methodology found appropriate for SC data. The NL model is more appropriate when the choices are interdependent and somewhat correlated [35]. For SC Model the choices will be bus, BRT, car & PPT and walk. The choices bus, BRT, car & PPT and walk are not interdependent to each other, so choice of nested logit (NL) model would not be appropriate. Again mixed logit (ML) model is more appropriate for panel data. For model calibrated with SC data ML model will not be appropriate as survey respondents were asked to choose only one choice for the work trip from the multiple choice scenario.

The choice set for model calibrated with SC data is:

- Bus (walk-bus-walk and walk-bus- rickshaw with average comfort level merged together to represent the current bus scenario)
- BRT (walk-bus-walk and walk-bus-rickshaw with good, better and best comfort levels merged together to represent the BRT system)
- Car & Personalized Passenger Transport (CPPT) (Rickshaw, CNG and Car merged together to represent CPPT)
- Walk (Walk represent to those who chose walk in the SC survey)

For selecting final attributes model with RP data has been considered and it has been described in the paper “Workers travel behaviour in the developing countries megacity considering Dhaka as a case study”. Model with RP data showed that gender, age, income, education, travel cost, and travel time in motion are the significant attributes for making mode choice decision in Dhaka. Table 5 lists attributes used in the model with the SC data.

TABLE 5 Attributes Used in the Model with SC data

Type of Attributes	Attributes	Description	Variable State	Coded Value
Mode Specific Attributes	Total Cost	Total money (in *BDT) workers spent for work trip		
	Time in motion by any vehicle or time by walking	Total time (in minute) workers are actually moving including any access time to/from public transport.		
Social Demographic Attributes	Income	Those who have income less than or equal to 5000 BDT are considered as Poor and those who has income more than 5000 BDT are considered as Not Poor	<=5000 *BDT	1
			>5000 *BDT	0
	Gender	Workers' Gender identity	Male	1
			Female	0
	Education	The sample is divided into those who have a postgraduate degree and those who do not have a postgraduate degree	With postgraduate education	1
			Without postgraduate education	0
	Age	The sample is divided into age less than or equal to 35 years and age above 35 years	<=35 YEAR	0
			>35 YEAR	1
Constant	Walk, car and CPPT Specific Constant			

*BDT= Bangladeshi Currency

Table 6 lists model estimation result for model calibrated with SC data.

TABLE 6 Model Estimation Result for Model Calibrated with Stated Choice Data

Type of Attributes	Attributes	Coefficient	Std. Err.	t-ratio	P-value
Generic Variable	Travel Time in Motion	-0.0661	0.0215	3.0701	<0.01
	Travel Cost	-0.0240	0.0048	4.9720	<0.01
Bus	Postgraduate	-2.3083	0.4495	5.1351	<0.01
	Gender	-0.6368	0.3679	1.7306	<0.01
BRT	Constant	0.8241	0.3822	2.1563	<0.01
	Income 0_5000	-3.4973	0.7584	-4.6115	<0.01
	Age Above 35	0.7129	0.3784	1.8842	<0.01
Car & PPT	Constant	0.7647	1.7094	0.4474	<0.01
	Postgraduate	3.2335	1.0516	3.0749	<0.01
	Age Above 35	2.0941	0.6264	3.3432	<0.01
Walk	Constant	-2.3830	1.0176	2.3418	<0.01
	Gender	-1.7716	0.5935	-.9853	<0.01
	Income 0_5000	3.9353	0.8039	4.8951	<0.01
	Age Above 35	1.4890	0.5245	2.8392	<0.01
Overall goodness of fit of the Model: Log Likelihood Function=-267.000 Pseudo R ² =0.43					

Table 6 shows that coefficients of generic travel cost and travel time in motion have expected negative signs. Both attributes were considered significant as their *t* statistics were greater than 1.96 at a 95% confidence level [36].

Postgraduate and gender are found as significant for the Bus mode. Both coefficients of postgraduate education and gender have a negative sign. Those who are poor and female tend to use bus more compared to their male counterparts.

The *t* statistics of the income and age attributes are significant for BRT mode. As the coefficient of the income 0-5000 attribute is negative, those who are poor usually will not choose BRT. As the coefficient of age attribute for 'BRT' mode is positive, mature age workers are likely to use 'BRT' mode for their work trip.

As the CPPT mode coefficient for postgraduate attribute is positive, those who have postgraduate education tend to choose 'car and PPT' mode. As the age coefficient for CPPT mode is positive, mature age workers who can afford choose car or PPT for the work trip are more likely to do so.

As the coefficient of gender for Walk mode is negative, female workers tend to choose Walk. Also, as the income 0-5000 coefficient for Walk mode is positive, those who are poor tend to choose 'walk' more than other modes. As the age coefficient for 'walk' mode is positive, those above the age of 35 would choose Walk for the work trip.

5. Model Validation

This section discusses model validation, includes the overall significance of the model, the prediction ability of the estimated model, and the correct prediction ability of the model.

5.1 Overall Significance of Model

To determine the overall significance of the model with SC data, a log likelihood ratio test was conducted (-2LL test) and Pseudo R^2 value was calculated.

If the log likelihood ratio value is less than critical chi square (χ^2) value at the 95% confidence level then the null hypothesis cannot be rejected (model is no better than the base model) (37). If the log likelihood ratio value is more than the critical χ^2 value at 95% confidence level then null hypothesis can be rejected (model is better than the base mode) (37). The -2LL value was determined to equal 396 while the critical χ^2 value was determined to equal 19.68 with 11 degrees of freedom at the 5 percent level of significance ($\alpha = 0.05$).

The pseudo R^2 value of the model was found to be 0.43, according to (35), which is equivalent to about 0.80 of linear R^2 . The results of -2LL and Pseudo R^2 value show that this model is significant.

5.2 Predictive Ability of Estimated Model

A comparison of the actual and the predicted mode share can provide the understanding of how the estimated model is performing. By comparing the actual mode shares with the predicted shares, the relative predictive abilities of the models can be determined (38, 39). For this research the comparison between the actual mode share and the predicted mode share was done in two ways:

- a) Applying utility functions over all individuals with their actual attributes, and
- b) Applying utility functions on a homogeneous groups of workers with sample average mode specific attributes

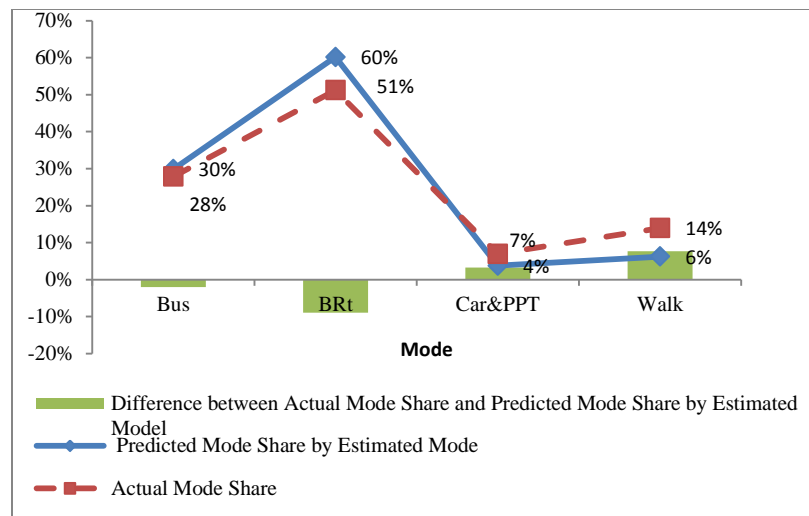
a) Applying utility function over all individuals with their actual attribute

This section describes comparison of actual mode share and the predicted mode share of the estimated model when the utility function is applied over all individuals with their actual attributes.

Figure 1 illustrates the comparison between actual and predicted mode share of the estimated model when the utility function is applied over all individuals with their actual observed mode specific attributes. The results in Figure 1 show that the model:

- underpredicts bus mode share to 2% less than actual mode share (in error by -7%),
- underpredicts BRT mode share to 9% less than actual mode share (in error by -15%),
- overpredicts car & PPT to 3% greater than actual mode share (in error by +50%), and
- overpredicts walk to 8% greater than actual mode share (in error by +50%).

Model result shows that there are no significant differences between actual and predicted mode share of bus and car & PPT. However the differences between observed and predicted mode share of both BRT and walk are more than 5%.



**Figure 1 Comparison of Actual and Predicted Mode Share
(Utility Function Applied over all Individuals)**

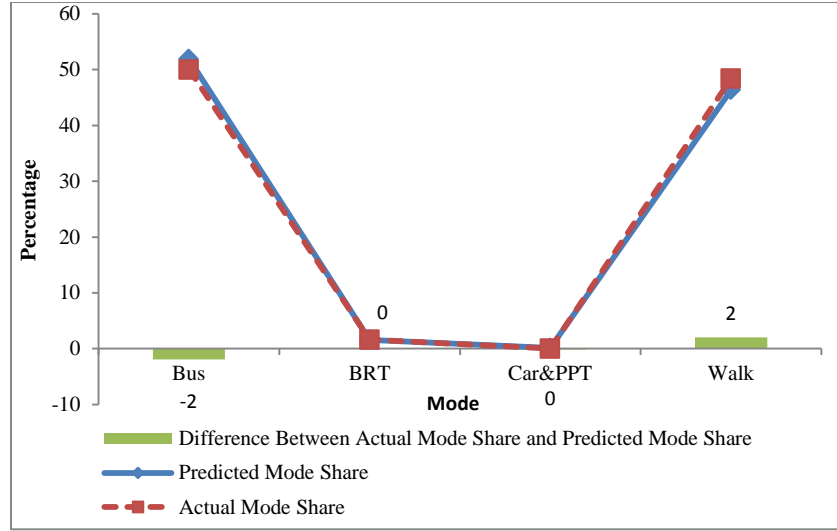
b) Applying utility function on a homogeneous group of workers with sample average mode specific attributes

Actual mode share and predicted mode share with estimated model was compared by applying utility functions on homogeneous groups of workers with sample average mode-specific attributes. The probability of mode share for each mode was calculated only once for a homogeneous group of workers with the average mode specific attributes.

Figure 2 illustrates the actual mode share and the predicted mode share of 'female workers without postgraduate education aged less than or equal to 35 and have income less than or equal to 5000 BDT'. The sample number of this group is 62. Figure 2 shows that the differences between the actual mode share and predicted mode share are small. Comparison shows that the model:

- underpredicts bus mode share to 2% less than actual mode share (in error by -4%);
- overpredicts walk mode share to 2% greater than actual mode share (in error by +4%);
- predicts BRT mode share accurate to actual mode share; and
- predicts Car & PPT mode share accurate to actual mode share.

Figure 2 shows that there are no significant differences between actual and predicted mode share. Comparing Figures 1 and 2 show that when utility functions are applied on a homogeneous group of workers with sample average, model predicts more accurately than utility function applied over all individual with their actual attributes.



**Figure 2 Comparing Actual and Predicted Mode Share
(Utility Function Applied on Homogeneous Group of Workers)**

5.3 Model's level of accuracy

The model's level of accuracy can be measured from the sign of the coefficients, log likelihood ratio test and its predictive ability. Some of the coefficients should have their intuitive sign, such as coefficients for travel time and travel cost always expected to be negative. According to (37, 42) if the model result does not provide the expected sign of coefficients then it is considered as invalid model. Coefficients for travel cost and travel time have the expected negative sign. The sign of the coefficients for other variables are also considered appropriate based on judgment; for example, it is expected that 'car' will be mainly used by those who have more income, mature aged and higher educational qualifications and the model result shows the same. All attributes are significant for the bus mode as t statistics for all attributes are higher than 1.96 at 95% significance level. However, the coefficient for gender attribute is slightly lower than 1.96 for bus mode. Log likelihood ratio test of the model shows that overall goodness of fit of the model is acceptable as -2LL values are greater than critical χ^2 value.

The predictive ability of the model can be portrayed from the comparison between predicted choice and actual choice. Train (38) and McFadden, Talvitie (40) compared the different model's predictive ability with the actual mode share. They considered the RMSE of different models to understand the predictive ability of the models.

Root Mean Square Error (RMSE) offers a unit less one number measure of forecasting accuracy (41). RMSE can take any positive value (0 to ∞). Therefore, any particular value of RMSE other than 0 does not provide any meaning. RMSE is used to compare two models. The unbiased model with the smallest RMSE value is considered as the best predictive model. Comparing RMSE with other studies would give indicative figures how accurately the model can predict. Equation 1 is used for calculating RMSE for the model (40). Table 7 lists the RMSE of model for application of utility function on different homogeneous groups of workers. McFadden, Talvitie (40) found in their research that their best predictive model has RMSE 9.534. The RMSE is closer to 0 for when utility function is applied to homogeneous group of workers. Result and discussion proves that the model's level of accuracy is acceptable for prediction.

$$RMSE = \sqrt{\sum (Q_i - R_i)^2}$$

Eq. 1

Where,
 $RMSE$ is root mean square
 Q_i is actual mode share of alternative i
 R_i is predictive mode share of alternative i

Table 7 Root Mean Square Error for the Model

Different Set for application of utility function	Root Mean Square Error
Utility functions applied to all individual with their actual attributes)	13.00
Utility function applied to “poor female without postgraduate education aged less than or equal to 35” (n= 62)	2.78

6. Elasticity Analysis for Dhaka

Table 8 lists elasticity of travel time in motion for all modes. Elasticity values of travel time in motion for all modes less than 1 reflects that all modes are relatively inelastic for the travel time in motion attribute. This is justifiable as this represent only work trip. Work trip is less elastic than other trip purposes (43).

Table 1 lists elasticity values for in-vehicle travel time for other cities for comparison. None of the published elasticity value has been found for travel time in motion defined as this research for public transport. However, elasticity of in-vehicle time from other studies will give indicative comparison with the elasticity value of travel time in motion for this research.

Travel time in motion in this research is defined as actual time commuters are moving and time to/from bus station. Literature review of in-vehicle time defined as time commuter actually moving for their trip. Direct and cross elasticity values for bus travel time in motion in the model calibrated with SC data are closely similar to elasticity value for bus in-vehicle travel time for developed cities.

Table 1 reveals that people in developed cities are elastic with BRT travel time. It can be assumed that commuters in developed cities would be more elastic with travel time in motion defined by this research because travel time in motion will be more than in vehicle travel time as it includes access time as well. SC model result for Dhaka showed that commuters are slightly elastic with respect to BRT travel time in motion. This could be due to commuters in developed countries being wealthier and having more travel options, so can switch to other modes of transport more easily when BRT travel time is increased.

As direct elasticity and cross elasticity values are less than 1, the modes are relatively less elastic to travel time in motion for CPPT. Increasing CPPT travel time in motion will increase the percentage of BRT more compared with each of Bus and Walk.

Table 1 reveals that, even though elasticities of car in-vehicle travel time for other cities do not include PPT, they can still enable an indicative comparison for elasticity of CPPT travel time in motion of the Dhaka SC model. The elasticity values of CPPT travel time in motion are very similar to elasticity values of car travel time in motion for developed cities.

Walk is relatively elastic with walk travel time in motion as the elasticity value is greater than 1. Commuters are slightly elastic with respect to walk travel time for Bus mode. However, workers are very inelastic with respect to walk travel time for each of the BRT and CPPT modes.

SC model result showed that workers are relatively elastic with walk travel time in motion. In some developed cities, such as in Minneapolis, USA, elasticity of walk travel time for walk varies from 0.14% to 0.26% (31). Minneapolis has a high quality transport system. The lower elasticity value of walk travel time in Minneapolis reflects people’s positive attitude toward walking. Contrarily commuters in Dhaka will be substantially sensitive with walk travel time increase.

TABLE 8 Elasticity of Travel Time in Motion

Mode	Bus	BRT	Car &PPT	Walk
Bus	-0.63	0.47	0.01	0.63
BRT	0.19	-0.37	0.05	0.03
Car & PPT	0.06	0.75	-0.45	0.04
Walk	0.50	0.06	0.01	-1.38

*Bold values indicate Direct Point Elasticity of the respective modes

Table 9 lists the elasticity of travel cost of Bus, BRT and CPPT for Dhaka. Direct and cross elasticity values of bus travel cost are less than 1 and very close to 0. Therefore, Bus, BRT, CPPT and walk are relatively inelastic with respect to bus travel cost. From the result it can be seen that of all modes, Walk mode share would increase the most with increasing bus travel cost. Most bus users who cannot afford increased bus fare will not switch to either BRT or CPPT. However, very small percentages of commuters would shift to BRT and CPPT in response to increased bus travel cost.

Table 2 lists elasticity values of different modes for different cities. The direct elasticity of travel cost of bus in developed cities varies from 0.15 to 0.65. The model result show that elasticity value of travel cost of bus for bus mode is lower than other cities. Workers are relatively inelastic with travel cost of bus in Dhaka compared with other cities.

Both the direct and cross elasticity of BRT travel cost are less than 1. Therefore, all modes are relatively inelastic with respect to BRT travel cost. Result shows that increased BRT travel cost would have the greatest increase in the probability of CPPT being chosen.

From Table 2 it can be seen that for Chicago the elasticity of travel cost of BRT is 0.17%, which is very similar to that of Dhaka. Both in developed city and in Dhaka commuters are slightly elastic with BRT travel cost. This may be because commuters would reap the benefits of improved BRT service.

As the direct elasticity of CPPT cost is greater than 1, these modes are relatively elastic to its travel cost. Car & PPT is the most expensive travel option for Dhaka. Therefore, commuters would react negatively if car & PPT cost were to increase. Result shows that with the increased car & PPT cost, the probability of choosing BRT will increase the most.

Direct elasticity of CPPT travel cost is considerably high. This is mainly because availability of improved travel options in SC scenario. Direct elasticity of travel cost of car for other cities showed that the values range from 0.23% to 0.32% (Table 2). For Tokyo this value is as low as 0.06%. Therefore, it can be said that in developed cities people are less sensitive to car travel cost than Dhaka city.

TABLE 9 Elasticity of Travel Cost

Mode	Bus	BRT	Car & PPT
Bus	-0.07	0.23	0.09
BRT	0.02	-0.19	0.43
Car & PPT	0.01	0.41	-3.61
Walk	0.05	0.03	0.05

*Bold values indicate direct point elasticity

7. Conclusion

Mode choice model developed with SC data showed that workers mode choice decision in Dhaka is highly influenced by travel cost, travel time in motion, income, age, education level and gender. Male and female commuters who are not poor would widely use BRT service for their work trip. However BRT would not be readily acceptable to poor commuters because of its high cost. Age and education has also significance influence on workers' BRT preference. Analysis showed that mature aged male workers who

are not poor with higher educational qualification have greater tendency to choose BRT for their work trip. It can be anticipated that for any developing city like Dhaka mode choice may have similar characteristics as Dhaka.

Comparison of elasticity value between Dhaka and developed cities showed similarities and differences of impact of change of attributes in the hypothetical BRT scenario. The presence of good transport system in the hypothetical BRT scenario makes Dhaka workers relatively more elastic with respect to bus travel time in motion. In a developed city people are also relatively more elastic with respect to bus travel time in motion. If bus travel time in motion increase those who can afford would switch to BRT and those who cannot would switch to walk mode. However, Dhaka commuters are very inelastic with general bus travel cost compared to those of developed cities. This may be because in the BRT scenario bus cost is considered as very low.

Interestingly because of less wealth and high cost of other modes Dhaka workers who would use BRT will be relatively less elastic with BRT travel time in motion and travel cost. Contrarily in the developed city people are relatively elastic with BRT or rapid transit travel time. However, in developed cities commuters are relatively less elastic with respect to BRT or rapid transit travel cost.

In Dhaka those who use car & PPT for their work trip would not change to other modes even though car & PPT travel time in motion increase. Contrarily as Dhaka workers are highly elastic with car & PPT travel cost, they would react significantly in negative manner with the increased car & PPT travel cost. However, in the developed city people would react negatively with the increase car travel time in motion as they are relatively elastic with car & PPT travel time.

Dhaka workers are highly elastic with walk travel time. On contrary in developed cities people show more positive attitude toward walk as they are relatively less elastic with walk travel time. People in developed countries treat walking as a way of doing physical exercise (not only a transport mode) while people in developing countries treat walking as purely a transport mode.

There is limited research on uptake of BRT in Dhaka considering work trip. This research significantly overcomes this gap by establishing probabilities of BRT usage across a range of socio-economic groups. Comparison between developed cities and the Dhaka BRT scenario would be beneficial in informing transport policy for any developing city. Future research will ascertain the choice of BRT for other trip purposes. This will also inform transport policy in any developing city.

The main limitation of this research is that elasticity from other cities did not combine in vehicle time with to/from bus station time. Another limitation of the model is application of the model as BRT is not in operation in Dhaka the model cannot be applied to justify the validation of the model. However, utility functions can be applied to forecast the future BRT ridership. Also this model will be useful to understand the important variable for BRT to be successful in Dhaka. Also this model has usefulness to understand how change of social demographic characteristics changes the people's preference to choose BRT and other modes. Another model has been developed with the RP data in the another paper. Comparison with RP model and SC model can provide indicative figure how changes would occur before BRT and after BRT operation. Result shows that about 55% current car users would switch to BRT, about 85% rickshaw users would switch to BRT, about 95% current bus users would continue using BRT, about 45% current walkers would switch to BRT, and about 82% current users who use laguna, taxi, tempo would switch to BRT.

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